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An Intelligent Tuned Harmony Search Algorithm for Optimum Design of Steel Framed Structures to AISC-LRFD

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Authors' contributions

This work was carried out in collaboration between all authors. Author MA established the theoretical basis of the work, followed the construction and performance of the developed design optimization model, contributed in the literature and analysis of the results. Author MA conducted a comprehensive literature review, developed the Methodology and contributed in the construction of the model and analysis of results. Author AK developed and verified the optimization model and contributed to the contribute in the literature and analysis of the results. All authors read and approved the final manuscript.

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ABSTRACT

Abstract: An optimum design of non-linear steel frames using an effective artificial intelligence algorithm is presented. To consider the actual behavior of steel connections, the studied steel frames were designed as semi rigid connections. The Frye and Morris polynomial model is used for modeling the non-linear behavior of the semi-rigid connections. In this work, the Intelligent Tuned Harmony Search (ITHS) optimization algorithm was implemented due to its efficiency in parameter initializing through maintaining a proper balance between diversification and intensification throughout the search process. The design algorithm obtains the minimum weight of steel frames by choosing from a standard set of the AISC steel sections. Strength constraints of American Institute of Steel Construction - Load and Resistance Factor Design (AISC-LRFD) specification, deflection, displacement, size constraint and lateral torsional buckling are imposed on frames. To demonstrate the application and validity of the algorithm, this paper presents two steel frames with extended end plate without column stiffeners. The results reflect the superiority of the ITHS

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algorithm in terms of accuracy, convergence speed, and robustness when comparing with the state-of-the-art harmony search algorithm (HS) and Genetic algorithm (GA).

Keywords: Optimum design; non-linear analysis steel frames; semi-rigid connections; fryeand morrismodel; harmony search; genetic algorithm.

1. INTRODUCTION

The processes of obtaining the optimum design of structures are very complicated to be solved by hand, due to the huge number of design variables. Typically, the design is limited by constraints such as choosing the material, feasible strength, displacements, deflection, size constraints, lateral torsional buckling and true behavior of beam-to-column connections. Generally, structural design optimization of steel frames requires a selection of steel sections for its beams and columns from a discrete set of practically available steel section tables. The design algorithm aims at obtaining minimum steel weight frames by selecting a standard set of steel sections such as AISC wide-flange W-shapes [1].

Computer-aided optimization has been used to achieve more economical designs since 1970s [2,3] and [4]. Numerous algorithms have been developed for accomplishing the optimization problems in the last four decades. Today's competitive world has forced engineers and designers to realize more economical designs and to search or develop more effective optimization techniques that's why heuristic search methods emerged in the first half of 1990s [5,6,7].

Recently, structural optimization witnessed the emergence of novel and innovative stochastic search techniques. These stochastic search techniques get the benefit by using the ideas which are taken from nature and are not suffered from the discrepancies of mathematical programming which depended on optimum design methods. Meta-heuristic algorithms eradicate some of the afore-mentioned difficulties and are quickly replacing the classical methods in solving practical optimization problems.

Meta-heuristic algorithms typically intend to find a suitable solution for any optimization problem by 'trial-and-error' in a reasonable amount of computational time. During the last few decades, several meta-heuristic algorithms have been proposed. These algorithms include:Genetic algorithms (GAs) [8] and [9], Genetic Programming [10], Evolutionary programming [11], Evolution strategies [12]. Ant colony optimization (ACO) [13,14], Particle Swarm Optimization (PSO) [15-18,19]. Artificial Bee Colony Algorithms (ABC) [20] and etc.

Harmony search (HS) algorithm is developed by Geem et al. [21] for solving optimization problems. HS bases on the analogy between the performance process of natural music and searching for solutions to optimization problems. The HS is simple in concept; easy in implementation; less in parameters and imposes fewer mathematical requirements [22]. The classical HS is good at identifying good regions in the search area within a reasonable time, but it is not efficient in performing the local search in numerical optimization applications [22].

To remove the drawbacks of different approaches of harmony search such as Improved HS (IHS), Global best HS (GHS) and Self Adaptive Harmony Search (SAHS) have been developed to improve the performance of the algorithm. An IHS was proposed by Mahdavi et al. [22], which dynamically updates some important parameters of the algorithm. Inspired by PSO, Omran and Mahadavi proposed GHS which generates new harmony by using best stored harmony at harmony memory [23]. Setting initial value for HS parameters can be considered as a challenging part of method. To mitigate this problem a SAHS algorithm was proposed by Wang and Huang [24], which obviate the necessity of allocating initial value to some parameters of HS.

A new variant called Intelligent Tuned Harmony Search (ITHS) algorithm is proposed by Yadav et al. [25]. It is based on the idea of balanced intensification and diversification; ITHS which borrows the concepts from the decision making depend on despotism, in which one dominant forms the group and makes the decision on behalf of that group. The pitch adjustment strategy, which adopted by the formed group, helps the algorithm in maintaining a proper balance between intensification and diversification within the bounded search space of the formed group. Meanwhile, the individuals who are not part of the dominant group follow the path of rebellion. Also, pitch adjustment strategy helps the algorithm search for a better solution than that of the worst individual in the Harmony Memory. Therefore, it enhances the explorative behavior of the algorithm.

The main differences between ITHS and GA can be summarized as: (i) ITHS generates a new design considering all existing designs, while GA generates a new design from a couple of chosen parents by exchanging the artificial genes; (ii) ITHS takes into account each design variable independently. On the other hand, GA considers design variables depending upon building block theory. (iii) ITHS does not code the parameters, whereas, GA codes the parameters. As well as, ITHS uses real value scheme, while GA uses binary scheme (0 and 1).

The main differences between ITHS and HS can be summarized as: (i) the self-adaptive pitch adjustment strategy adopted by the dynamic sub-populations based on the consciousness (Harmony Memory) helps the algorithm in maintaining the proper balance between diversification and intensification throughout the search process, while the HS algorithm uses a stochastic random search that is based on the harmony memory considering rate and the pitch adjusting rate (defined in harmony search meta-heuristic algorithm section); (ii) the value of a neighboring index bandwidth change dynamically (large initially and decrease gradually with iterations), this suggestion would help the algorithm to diversify the search space of the solution vectors and prevent the solution from getting trapped in local minima. Moreover, HS takes a random of the neighboring index. The intelligent group formation and novel harmony improvisation scheme adopted by the ITHS algorithm are different from the other sub-population approaches adopted by GA and HS algorithms. Also, reducing the number of setting parameters makes ITHS an ideal method to coping with complex engineering optimization problems.

Not long ago, a large number of optimum structural design algorithms have been developed which are relied on these effective, powerful and novel techniques such as Genetic algorithm based optimum design of nonlinear planar steel frames with various semi-rigid connections [26], Design of steel frames using ant colony optimization [27], Harmony search algorithm for minimum cost design of steel frames with semi-rigid connections and column bases [28] and Optimum design of cellular beams using harmony search and particle swarm optimizers [29].

There are numerous applications of these heuristic optimization methods to various engineering optimization problems such as ensemble strategies with adaptive evolutionary programming [30], A New Image Thres holding Method Based on Gaussian Mixture Model [31], Artificial Neural Network simulation of hourly groundwater levels in a coastal aquifer system of the Venice lagoon [32], Application of a PSO-based neural network in analysis of outcomes of construction claims [33], a new hybrid algorithm for optimal reactive power dispatch problem with discrete and continuous control variables [34], a novel hybrid algorithm of imperialist competitive algorithm and teaching learning algorithm for optimal power flow problem with non-smooth cost functions [35], a comparative study: modified teaching learning algorithm and double differential evolution algorithm for optimal reactive power dispatch problem [36], an application of imperialist competitive algorithm with its modified techniques for multi-objective optimal power flow problem [37], a new hybrid bacterial foraging and simplified swarm optimization algorithm for practical optimal dynamic load dispatch [38] and improving transient stability with multi-objective allocation and parameter setting of Static Var Compensator (SVC) in a multi-machine power system [39].

The current study develops an algorithm to obtain the optimum design of steel frames with semi-rigid beam-column connections to represent the actual behavior of these connections. Among the artificial intelligent technique which mentioned earlier, the Intelligent Tuned Harmony Search (ITHS) was chosen due to its powerfulness in terms of accuracy, convergence speed, and robustness, comparing with the state-of-the-art harmony search algorithm (HS) and Genetic algorithm (GA). There are several models to simulate the behavior of semi rigid frame connections such as Linear, Exponential, Cubic B-spline, Power and Frye and Morris Polynomial model. The Frye`s and Morris`s model is a nonlinear one which represents the moment-rotation behavior of a connection effectively. This model is wildly used due to its effectiveness and simplicity.

While demonstrating the application of the developed algorithm by presenting two steel frames with extended end plate moment connections. The results of the current study were compared with genetic algorithm (GA) technique as GA is one of wildly applied technique in design optimization of steel structures also the current results were compassion with the basic harmony search technique in order to prove the super priority in terms of accuracy, convergence speed, and robustness when comparing with Intelligent Tuned harmony search algorithm (ITHS). Whatever, the design optimization problem was formulated to obtain the minimum steel frame weight. The AISC-LRFD specifications were imposed on the strength, displacement, deflection, size constraints and lateral torsional buckling are imposed on frames.

2. INTELLIGENT TUNED HARMONY SEARCH ALGORITHM

Harmony Search technique (HS) was proposed by [21,40-42,43] for working out combinatorial optimization problems. This approach is based on the musical performance process that takes place when a musician searches for a better state of harmony. A new variant of Harmony Search is intelligent tuned harmony search algorithm (ITHS) which proposed by [25]. A brief description of the implementation steps of the ITHS technique is presented as follow:

2.1 Step. 1 ITHS Parameters

The ITHS technique comprises several parameters to identify an algorithm which better represents a specific problem. These parameters comprise harmony memory (HM) matrix, harmony memory size (HMS), harmony memory consideration rate (HMCR), pitch adjustment rate (PAR), minimum pitch adjustment rate (PAR_{min}), maximum pitch adjustment rate (PAR_{max}), random uniformly distribution (rand), design variables (X_{sl}), lower bound ($_{L}X_{i}$), upper bound ($_{u}X_{i}$), iteration number (iter) and stopping criteria (Max_{iter}).

2.2 Step. 2 Initialize Harmony Memory

In this step the harmony memory matrix is initialized by random selection of design variables from the adopted steel section list. The random selection is performed by using the interval [0,1]. The HM matrix can be represented as shown below:-

$$HM=\begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{ng-1}^1 & x_{ng}^1 \\ x_1^2 & x_2^2 & \cdots & x_{ng-1}^2 & x_{ng}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{HMS-1} & x_2^{HMS-1} & \cdots & x_{ng-1}^{HMS-1} & x_{ng}^{HMS-1} \\ x_1^{HMS} & x_2^{HMS} & \cdots & x_{ng-1}^{HMS} & x_{ng}^{HMS} \end{bmatrix} \begin{matrix} \rightarrow & \varphi(x^1) \\ \rightarrow & \varphi(x^2) \\ \rightarrow & \vdots \\ \rightarrow & \varphi(x^{HMS-1}) \\ \rightarrow & \varphi(x^{HMS}) \end{matrix} \quad (1)$$

Where, x_i^1, x_i^2,…, x_i^{HMS-1},x_i^{HMS} and $\varphi(x^1)$,$\varphi(x^2)$,…, $\varphi(x^{HMS-1})$, $\varphi(x^{HMS})$ are design variables and the corresponding unconstrained objective function value, respectively. The Harmony Memory (HM) matrix is treated like an organization, the first step is to identify a leader. The leader is chosen based on the objective function value of each solution vector and is represented by$\varphi(x)^{best}$, where best is the index of the best harmony in the (HM). The Harmony Memory is divided into two groups (sub-populations), Group A and Group B. Group A consists of all the solution vectors whose objective function value is less than or equal to HM^{mean}, and Group B consists of the rest. HM^{mean} is the mean of the objective function values of the whole HM. Group A is responsible for both intensification and diversification, whereas Group B is responsible only for diversification.

2.3 Step. 3 Improvise a New Harmony

A new harmony solution vector x_i^{new} is improvised from either the HM or entire section list which based on HMCR, PAR, rand as follows.

$$x_i^{new} \leftarrow \begin{cases} x_i^{new} \in \ HM(d,i) \quad \text{with probability HMCR} \\ \quad \text{where, } d = (1+(HMS-1).\,rand[0,1] \\ \quad \text{Note: } d \ \text{integer number} \\ x_i^{new} \in x_{sl} \quad \text{with probability } (1-HMCR) \end{cases} \quad (2)$$

The ITHS algorithm dynamically updates the value of parameter PAR as the iterations process proceeds as shown in Equation 3.

$$PAR = PAR_{max} - (PAR_{max} - PAR_{min}).\,(\frac{iter}{Max_{iter}}) \quad (3)$$

Where, the iteration process (iter) starts from 1 until satisfying the stopping criteria (Max_{iter}). The values of minimum pitch adjustment rate PAR_{min} and maximum to pitch adjustment rate PAR_{max} are fixed to 0 and 1, in turn. Wang & Huang [24] suggested that the value of the parameter PAR should be decreased through time to prevent overshooting and oscillations, whereas the value of parameter bandwidth (bw) should be large initially. This suggestion would help the algorithm to diversify the search space of the solution vectors and prevent the solution from getting trapped in local minima.

The Harmony Memory improvisation for the selected x_i^{new} is determined by the group to which it belongs to. The new x_i^{new} of the i^{th} design variable will be chosen as a discrete value between the lower bound ($_LX_i$) to the upper bound ($_uX_i$) of design variables (X_{sl}). If the objective function value of HM (d,i)is less than or equal the harmony memory mean HM^{mean}, the pitch adjustment of the selected x_i^{new} is given by Equation 4.

$$x_i^{new} \leftarrow \begin{cases} x_i^{best} - (x_i^{best} - x_i^{new}).\ rand[0,1] & \text{with probability } 0.5.PAR \\ x_i^{best} + (x_i^{worst} - x_i^{new}).\ rand[0,1] & \text{with probability } 0.5.PAR \\ x_i^{new} & \text{with probability } (1-PAR) \end{cases} \quad (4)$$

Where, x_i^{best} and x_i^{worst} denote the i^{th} variable of the best and the worst solution vectors, respectively, from the HM evaluated in terms of the objective function from the previous iteration's experience. Therefore, the pitch adjustment is based on the consciousness (Harmony Memory) of the search.

In the early stage, there is a need for optimum balance between intensification and diversification. In addition, the pitch adjustment strategy, which was adopted in Group A, cares of both the intensification and diversification of the search. The term x_i^{best}- (x_i^{best}- x_i^{new}). Rand [0,1] allows the selected x_i^{new} to search between itself and x_i^{best}in the search space. Here, the search is governed by the attractiveness of the objective function of x_i^{best}, so this pitch adjustment strategy is mainly responsible for the intensification of the search.

The other term, x_i^{best}+ (x_i^{worst} - x_i^{new}). rand [0,1], is responsible for the diversification of the search. If the selected x_i^{new} is closer to x_i^{worst}, then the term (x_i^{worst}-x_i^{new}) is smaller. Therefore, the value of x_i^{best} + (x_i^{worst} - x_i^{new}). Rand [0,1], is closed to x_i^{best}, and the selected $x_i^{new}$is forced to move closer to x_i^{best}. However, if the selected x_i^{new} is far from x_i^{worst}, then the value is forced to move farther from x_i^{best}. Moreover, this pitch adjustment strategy mainly governs the diversification of the search and helps the algorithm in maintaining a proper balance between intensification and diversification.

The search space of Group A is bounded by x_i^{best} and x_i^{worst} and therefore, there is a probability that the ITHS algorithm may converge to a local optimum solution if the optimum solution lies outside the defined boundary of Group A. Furthermore, to overcome this bounding, it is necessary to enhance the diversification of the ITHS algorithm. As a result, Group B is formed, and if the selected x_i^{new} belongs to Group B, it becomes responsible for enhancing the diversification of the search. Whatever, Selecting x_i^{new} randomly selects the decision variable from the solution vector corresponding to $\varphi(x)^{best}$ and starts the search in its neighborhood. The pitch adjustment strategy adopted in Group B is similar to that of a rebellion. The pitch adjustment for the selected x_i^{new} is given by.

$$\begin{aligned} & x_i^{new} \leftarrow \{ \quad x_i^{new} - ((x_m^{best})' - x_i^{new}).\ rand\ [0,1] \\ & \quad \text{where },\ m = (1 + (ng - 1).\ rand\ [0,1]) \\ & \quad \text{Note : m integer number} \\ & \quad ng = \text{total number of groups.} \end{aligned} \quad (5)$$

The bound checking criterion follows this step; it leads to inefficient use of iterations in such problems. The method proposed by (Yadav, et al.) [25], to ensures that x_m^{best} is located between in its lower bounds $_LX_i$ and upper bounds $_uX_i$ of the i^{th} decision variable. Because x_m^{best} is in the range of lower $_LX_m$ and upper bounds $_uX_m$ of m in the harmony memory and it can be expressed by Equation 6, where, Δ_m is between 0 and 1. Similarly, $(x_m^{best})'$ can be expressed by.

$$x_m^{best} = {}_Lx_m + ({}_ux_m - {}_Lx_m)\,\Delta_m \quad (6)$$

$$(x_m^{best})' = {}_Lx_i + ({}_ux_i - {}_Lx_i)\,\Delta_m \quad (7)$$

Using Equations 6 and 7, $(X_m^{best})'$ can be expressed as

$$(x_m^{best})' = {}_Lx_i + ({}_ux_i - {}_Lx_i)\,.\,\frac{(x_m^{best} - {}_Lx_m)}{({}_ux_m - {}_Lx_m)} \quad (8)$$

2.4 Step. 4 Update the Harmony Memory

If the new Harmony is better than the worst design in the HM, the new design is included in the HM and the existing worst harmony is excluded from the HM.

2.5 Step. 5 Termination Criteria

Steps 3 and 4 are repeated until the termination criterion is satisfied. If the worst objective function $\varphi(x)^{worst}$ in HM is equal the $\varphi(x)^{best}$ the search space is closed automatically and the optimal design is achieved.

3. FORMULATION OF THE OPTIMIZATION PROBLEM

The formulation of the current problem as an optimization problem is carried out by identifying the design variables, objective function, penalized objective function and penalty function as follows:

3.1 Design Variables

Structural design optimization of steel frames generally requires selection of steel sections for its beams and columns from a discrete set of practically available steel section tables. The design algorithm aims at obtaining the minimum steel weight of frames by selecting a standard set of steel sections. The current study utilizes the AISC wide-flange shapes from W40 to W8 as the design variables of the optimization problem. These sections are considered the most practical sections for steel beams and columns.

3.2 The Objective Function

The adopted discrete optimization problem of the design of steel frames is to minimize the overall steel weight. The objective function of the minimization problem is formulated as follows:

$$\text{Minimize} \quad W(x) = \sum_{K=1}^{ng} A_k \sum_{i=1}^{mk} \rho_i L_i \qquad (9)$$

In Equation 9, W(x) is the total weight of the members, ng is total numbers of groups in the frame, mkis the total numbers of members in group k, A_k is cross-sectional area of member group k, ρ_i and L_i are density and length of member i.

3.3 Penalized Objective Function

In order to assess the fitness of a trial design and determine its distance from the global optimum, the eventual constraint violation should be computed by means of a penalty function. The penalty function consists of a series of geometric constraints corresponding to the dimensions and shape of the cross sections, and a series of constraints related to the deflection and internal forces of the members of the structure. Thus, the penalty is proportional to constraint violations, and the best design has the minimum weight with no penalty. There are several studies devoted to the selection of penalty functions [44-45,46]. In this study, the penalized objective function φ(x) is applied and written for American Institute of Steel Construction Load and Resistance Factor Design (AISC-LRFD) code as follows [1]:

$$\varphi(x) = W(x) \,.\, (1 + KC)^{\varepsilon} \qquad (10)$$

Where,

Φ(x) = penalized objective function, W(x) = total weight of the members, K = penalty constant, C= constraint violation function and ε= penalty function exponent. In this study K= 1.0, ε =2.0 are considered [27].

3.4 Penalty Function

The constraints of the current optimization problem comprise displacement constraints, size constraints, deflection constraints and strength constraints. Therefore, the constraint violation function of the optimization problem is expressed as [47]:

$$C = \sum_{i=1}^{N_{jt}} C_i^{td} + \sum_{i=1}^{N_s} C_i^{id} + \sum_{i=1}^{N_{cl}} C_i^{sc} + \sum_{i=1}^{N_f} C_i^{sb} + \sum_{i=1}^{N_f} C_i^{db} + \sum_{i=1}^{N_c} C_i^{I} \qquad (11)$$

Where,

C_i^{td} is constraint violations for top-storey displacement, C_i^{td} is constraint violations for inter-storey displacement, C_i^{sc} and C_i^{sb} are constraint violations for the size constraints column and beam, respectively, C_i^{td} is constraint violations for beam deflection and C_i^{I} the interaction formulas of the LRFD specification; N_{jt}= number of joints in the top storey. N_s and N_c= number of stores except the top story and number of beam columns, respectively. N_{cl}= the total number of columns in the frame except the ones at the bottom floor. N_f = number of storeys. The computation of the penalty function of these constraints is illustrated below: The penalty may be expressed as,

$$C_i = \begin{cases} 0 & \text{if} \quad \lambda_i \leq 0 \\ \lambda_i & \text{if} \quad \lambda_i > 0 \end{cases} \quad (12)$$

The displacement constraints are,

$$\lambda_i^{td} = \frac{d_t}{d_t^u} - 1.0 \leq 0 \quad \text{where} \quad i = 1,....N_{jt} \quad (13)$$

$$\lambda_i^{id} = \frac{d_i}{d_i^u} - 1.0 \leq 0 \quad \text{where} \quad i = 1,....N_s \quad (14)$$

Where,

d_t: maximum displacement in the top storey, d_t^u: allowable top storey displacement (max height/300), d_i : inter-storey displacement in storeyi, d_i^u: allowable inter-storey displacement (storey height /300).

The size constraint is given as follows,

$$\lambda_i^{sc} = \frac{d_{un}}{d_{bn}} - 1.0 \leq 0 \quad \text{where} \quad i = 1,....N_{cl} \quad (15)$$

$$\lambda_i^{sb} = \frac{d_{bf}}{d_{bc}} - 1.0 \leq 0 \quad \text{where} \quad i = 1,....N_f \quad (16)$$

Where,

d_{un} and d_{bn} are depths of the steel sections selected for upper and lower floor columns, d_{bf}, d_{bc} are the width of the beam flange and the column flange in turn.

The deflection control for each beam is given as follows,

$$\lambda_i^{db} = \frac{d_{db}}{d_{du}} - 1.0 \leq 0 \quad \text{where} \quad i = 1,....N_f \quad (17)$$

Where,

d_{db}: maximum deflection for each beam, d_{du}: allowable floor girder deflection for un-factored imposed load ≤ unbraced Length/360.

4. STRUCTURAL DESIGN REQUIREMENTS OF STEEL MEMBERS

The adopted strength constraints based on AISC-LRFD [1] are expressed in the following sections.

4.1 For Members Subjected to Bending Moment and Axial Force

$$\text{for} \quad \frac{P_u}{\varphi_c P_n} \geq 0.20$$

$$\lambda_i^I = \left(\frac{P_u}{\varphi_c P_n}\right) + \frac{8}{9}\left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) - 1.0 \leq 0$$

$$\text{where} \quad i = 1,....N_c \quad (18)$$

$$\text{for} \quad \frac{P_u}{\varphi_c P_n} < 0.20$$

$$\lambda_i^I = \left(\frac{P_u}{2\varphi_c P_n}\right) + \left(\frac{M_{ux}}{\varphi_b M_{nx}} + \frac{M_{uy}}{\varphi_b M_{ny}}\right) - 1.0 \leq 0$$

$$\text{where} \quad i = 1,....N_c \quad (19)$$

Where,

P_u = factored applied compression load, P_n = nominal axial strength (compression), M_{ux} = factored applied flexural moment about the major axis, M_{uy}= factored applied flexural moment about the minor axis, M_{nx}= nominal flexural strength about the major axis, M_{ny} = nominal flexural strength about the minor axis (for two-dimensional frames, M_{uy} = 0), φ_c= resistance factor for compression (equal 0.90), φ_b =flexural resistance factor (equal 0.90).

4.1.1 The nominal compressive strength of a member

$$P_n = A_g F_{cr} \quad (20)$$

$$F_e = \frac{\pi^2 E}{(KL/r)^2} \quad (21)$$

$$F_{cr} = 0.658^{(F_y/F_e)} F_y \quad \text{when}, \quad \frac{F_y}{F_e} \leq 2.25 \quad (22)$$

$$F_{cr} = 0.877 F_e \quad \text{when}, \quad \frac{F_y}{F_e} > 2.25 \quad (23)$$

Where,

P_n = nominal axial strength (compression), A_g = cross-sectional area of member, F_{cr} = critical compressive stress, F_e = Euler stress, F_y = yield stress of steel, E =modulus of elasticity, K=effective-length factor, L= member length, r =governing radius of gyration. The effective length factor K, for an unbraced frame is calculated from the following approximate equation (equation 24) taken from [48]. The out-of-plane effective length factor for each column member is specified to be Ky=1.0, while that for each beam member is specified to be Ky= L/6 (i.e., floor stringers at L/6 points of the span). The length of the unbraced compression flange for each column member is calculated during the design process, while that for each beam member is specified to be L/6 of the span length.

$$K = \sqrt{\frac{1.6G_A G_B + 4.0(G_A + G_B) + 7.50}{G_A + G_B + 7.50}} \quad (24)$$

Where,

Subscripts A and B denote the two ends of the column under consideration. The restraint factor G is stated as the following:

$$G = \frac{\sum (I_c/L_c)}{\sum (I_B/L_B)} \quad (25)$$

Where,

I_c is the moment of inertia and L_c is the unsupported length of a column section; I_B is the moment of inertia and L_B is unsupported length of a beam section. Σ indicates a summation for all members connected to that joint (A or B) and lying in the plane of buckling of the column under consideration.

4.1.2 The nominal flexural strength of a member

Design strength of beams is $\varphi_b M_n$. As long as $\lambda \le \lambda_p$, the M_n is equal to M_p and the shape is compact. The plastic moment M_p is calculated from the following equation.

$$M_n = M_p = F_y z_x \quad (26)$$

Where,

M_n = nominal flexural strength, M_p = plastic moment, F_y= yield stress of steel, Z= the plastic section modulus, λ_p= slenderness parameter to attain M_p. φ_b =flexural resistance factor (equal 0.90). Details of the formulations are given in the AISC-LRFD [1].

4.2 Modeling of Steel Frame Structures with ANSYS

In this study, ANSYS software was used to model various elements and connection of steel structures. The beams and columns of the frame were modeled using BEAM3, from ANSYS library elements. BEAM3 is a uniaxial element with tension, compression, and bending capabilities. This element has three degrees of freedom at each node: translations in the nodal x and y directions and rotation about the nodal z-axis.

The steel connections of the frame were simulated using a non-linear spring element, COMBIN39, which is considered a unidirectional element with nonlinear generalized force-deflection capabilities that can be used in any analysis. The element is defined by two (preferably coincident) node points and a generalized force-deflection curve. The points on this curve represent force (or moment) versus relative translation (or rotation) for structural analysis.

4.3 Modeling and Analysis of Steel Frame Connections

In the present study, the extended end plate connections without column stiffeners will be used to connect the columns and beams, as well as, the extended end plate connections were modeled using the COMBIN39, by applying Frye-Morris polynomial model [49] as shown in Equation 27.

$$\theta_r = c_1(KM)^1 + c_2(KM)^3 + c_3(KM)^5 \quad (27)$$

Where,

θ_r is a rotation (rad x10^{-3}), M is a moment connection (Kip.in), K is a standardization constant which depends upon connection type and geometry; c_1, c_2, c_3 are the curve fitting constants. The values of these constants are given in Table 1. [50].

The non-linear analysis of steel frames takes into account the geometrical non-linearity of beam-column members and non-linearity due to the end connection flexibility of beam members. The geometry and size parameters of the extended end plate connections without column stiffeners are presented in Fig. 1.

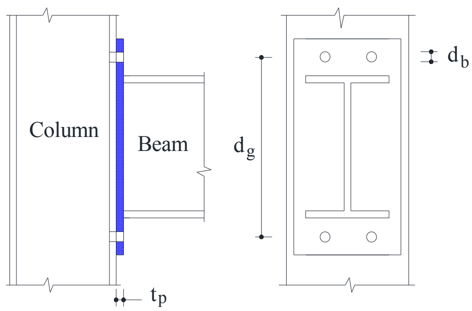

Fig. 1. Extended end plate without column stiffeners

4.4 Design Examples

Two design problems were checked in the current study to imply the developed optimum design algorithms. Moreover, the design of steel frames with semi-rigid connections was compared with rigid connections under the same design requirements. Semi-rigid and rigid connections frames were analyzed linearly and non-linearly including P-Δ effect of beam-column members. The design algorithm aims at obtaining the minimum steel weight of frames by selecting a standard set of steel W-sections from the AISC standard sections. AISC strength, displacement, deflection and size constraint for all members and lateral torsional buckling were also imposed on frames [1].

A comparison study was carried out between the ITHS optimization results and the results obtained from similar frames optimized using Harmony Search (HS) and Genetic Algorithm (GA) techniques which were published by [26,47].

The adopted evaluation criteria for comparison of the obtained results are the minimum weight which represents the cost of the structure and the number of iterations which represents the time needed to reach the optimal design by the algorithm.

4.5 Three-storey, Two-bay Steel Frame

The geometry and loading of a three-storey, two-bay frame are shown in Fig. 2. The columns in a story are collected in two member groups as outer columns and inner columns, whereas beams collected in one groups as inner beams. The outer columns are grouped together as having the same section every storey as shown in Fig. 2. The beam - columns are selected from the AISC wide-flange W-shape profile list. The frame is subjected to various gravity loads in addition to lateral forces. The gravity loads acting on a beam, which are applied as uniformly distributed loads. All the floors, except the roof, are subjected to a design load of 0.22 Kips/in and the beams of the roof level are subjected to the design load 0.17 Kips/in. In addition, the lateral forces applied on the joints 8 kips for all storeies except the roof joints [26,47].

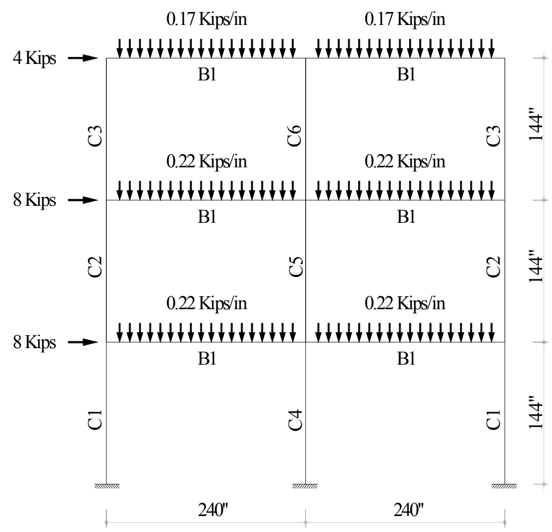

Fig. 2. Three-storey, two-bay steel frame

The Modulus of Elasticity and Yield stress of the steel sections are 29,000 ksi and 36 ksi, respectively. The top storey and inter-storey sway (H/300) is limited to 1.44 inch, 0.48 inch, in turn. The allowable deflection for service imposed load (L/360) is considered 0.66 inch. The out-of-plane effective length factor for each column (Ky) is taken 1.0. The out of plane unbraced length (L/6) for beamsis specified to be 40 inch. Bolt diameter and end plate thickness are taken to be 1 inch, 0.685 inch, respectively [47].

Due to the existence of several unknown starting values of ITHS parameters, a large number of trials were carried out to identify the adequate starting level of each parameter. Accordingly, the harmony memory size (HMS) and the harmony memory consideration rate (HMCR) are selected as 15 and 0.99, respectively. The minimum and maximum pitch adjustment rate PAR_{min} and PAR_{max} are taken as 0 and 1 respectively, the max improvisation (Max_{iter}) is 2500 i^{th}. The harmony search (HS) parameters are used as follows; HMS = 15, HMCR = 0.90, PAR = 0.45, bandwidth (bw) with a randomly selected neighboring index of -2 or +2, for example, if x_i^{new} is W14X68, the neighboring index of -2 or +2 forms a list of W14x90, W14x82, W14x74, W14x68, W14x61, W14x53, W14x48. The algorithm chooses a random neighbor section from the four sections, namely; W14x82, W14x74 or W14x61, W14x53) [47].

The results of ten independent runs of the ITHS steel design optimization algorithm are presented in Table 2. It is observed that the non-linear analysis including p-Δ effect of semi-rigid connection frames showed 6.06% less steel weight than those with rigid connections. The optimum weight converged at 1419th iterations after 55 minutes with a personal computer specification (Processor: Intel (R) core (TM) i7 CPU, Installed memory: 6.00 GB, System type: 64-bit operating system). This means that the convergence was obtained using only 56% of the expected max improvisation (Max_{iter}), 2500.

In addition, the solution with linear analysis of semi-rigid connections yielded 4.98% lighter frame weight than those with rigid connections and the optimum weight converged at 1353th iterations was obtained using only 54% of the expected max improvisation (Max_{iter}), 2500. Over the above, Table 2 revealed that in all cases of the ITHS 2.11% - 3.05% mean absolute percentage error (MAPE) was obtained, which reflected the accuracy of the algorithm technique.

Fig. 3 shows a typical convergence history for an ITHS design of a three-storey, two-bay, steel frames with semi-rigid connections for the best solution. As shown in this figure, the optimization process decreased gradually to fine-tune. This is achieved due to the fact that the values of pitch adjustments PAR and bandwidth (bw) decrease with time to prevent overshoot, oscillations and forcing the algorithm to focus more on intensification in the final iterations.

To demonstrate the search behavior of the ITHS algorithm, Fig. 4 shows the variation in the size grouping of the Harmony Memory (HM) matrix. Fig. 4 reveals that the Harmony Memory mean (HM^{mean}) smoothly decreases with iteration progress. Moreover, the convergence curve showed that the difference between group A (intensification and diversification) and group B (diversification only) was high up to the iteration number 800th. This difference between group A and B diminished gradually beyond the iteration 800th, resulting in one value represents the harmony memory mean. This value was obtained at the iteration number 1419th and kept unchanged until the 1555th iteration. The extra iterations performed beyond the 1419th iteration were carried out by the algorithm to ensure that no other minimums can be found.

The optimum steel sections designations obtained by the current Intelligent Tuned Harmony Search (ITHS) method – the GA results obtained by Kameshki and Saka [26] and the HS results khalifa [47] are given in Table 3. Table 3 presents also the optimum frames having rigid and semi-rigid connections analyzed linearly and nonlinearly. In general, the semi-rigid frame indicated less weight than that of frames with rigid connections. The optimum weight of semi-rigid frames obtained using ITHS was 2.67% which is lower than those obtained by harmony search technique (HS). In addition, Table 3 revealed that in all cases ITHS yielded lighter frames ranging between 2.46% - 6.06% compared with those obtained by HS [47].

When comparing the results of ITHS with the corresponding frames optimized using genetic algorithm (GA) technique, the ITHS indicated 13.54% lighter weights than those optimized using GAs. Furthermore, Table 3 revealed that in all cases ITHS yielded lighter frames between 13.54% - 33.54% compared with those obtained by GAs [26].

Table 1. Curve fitting constants and standardization constant

Connection types	**Curve fitting constants unit (inch)**	**Standardization constant unit (inch)**
Extend end plate without column stiffeners	$c_1 = 1.83 \times 10^{-3}$ $c_2 = 1.04 \times 10^{-4}$ $c_3 = 6.38 \times 10^{-6}$	$K = d_g^{-2.4}\, t_p^{-0.4}\, d_b^{-1.5}$

Table 2. Minimum steel frame weight of three-storey, two-bay steel frame based on ITHS

Frame analysis no.	Rigid connection				Semi-rigid connection			
	Linear analysis		Non-linear analysis plus P-Δ effect		Linear analysis		Non-linear analysis plus P-Δ effect	
	Weight lb	Iteration no.i^{th}	Weight lb	Iteration no.i^{th}	Weight lb	Iteration no.i^{th}	Weight lb	Iteration no.i^{th}
1	6504	1336	6528	1124	6180	1353	6132	1419
2	6528	1242	6648	1599	6264	1019	6156	1381
3	6552	1502	6696	1717	6288	1206	6192	996
4	6600	1100	6720	1639	6324	1484	6216	1473
5	6624	1676	6768	1234	6408	1564	6240	1108
6	6672	1410	6780	1310	6420	1270	6336	1644
7	6684	1394	6792*	1072	6432	1484	6348	1138
8	6744	1579	6792*	1535	6456	1433	6360	1537
9	6756	1317	6804	1825	6480	1599	6396*	1419
10	6792	1690	6816	1005	6492	1606	6396*	1549
Min weight (Ib)	6504	-	6528	-	6180	-	6132	-
MAPE(%)	2.11	-	3.05	-	3.03	-	2.29	-
Time(min)	23		45		30		55	

*Note: 1- The * symbol have the same weights but different sections. 2- Mean absolute percentage error (MAPE) =*

$$\frac{100\ \%}{n}\sum_{i=1}^{n}\frac{|\text{Actual value - Minimum value}|}{|\text{Actual value}|}$$

Where, n = Frame analysis Number

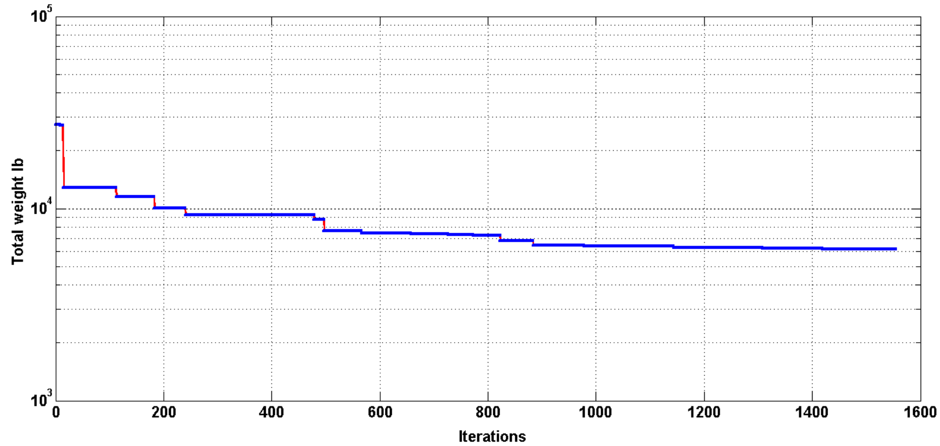

Fig. 3. Optimum design history for three-storey, two-bay steel frame

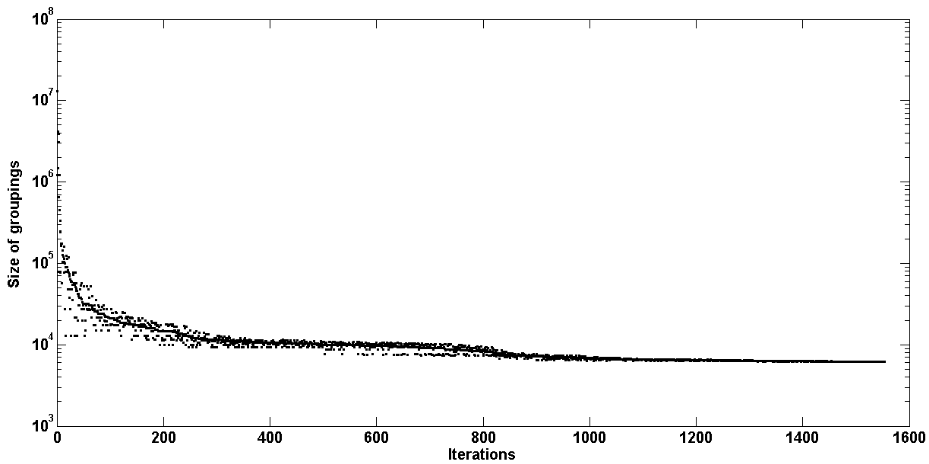

Fig. 4. Size of Grouping with iterations for three-storey, two-bay steel frame

The results also showed that the lateral displacement at the top storey was 1.18 inch in case of non-linear semi-rigid frame, which is higher than those obtained by HS and GAs, but within the allowable limit of AISC-LRFD (1.44 inch) [1]. This can be attributed to the fact that lighter sections will sway more than heavier members.

The obtained results of the ITHS optimization reflect the superiority of this algorithm in terms of accuracy, convergence speed, and robustness when compared with HS and GAs.

4.6 Ten-storey, One-bay Steel Frame

The geometry and loading of a ten-storey, one-bay frame are shown in Fig. 5. That is, the columns in a story are collected in one member groups as outer columns, whereas beams are one group as inner beams. The columns are grouped together as having the same section over two adjacent stories, and the beams are grouped together as having the same section over three adjacent stories except the roof level beam as shown in Fig. 5.

The beam - columns are selected from the AISC wide-flange W-shape profile list. The frame is subjected to various gravity loads in addition to lateral forces. The gravity loads acting on a beam, which are applied as uniformly distributed loads. All the floors, except the roof, are subjected to a design load of 0.50 Kips/in and the beams of the roof level are subjected to the design load 0.25 Kips/in. In addition, the lateral forces applied on the joints 2.50 kips for all storeies except the roof joints 1.25 kips [26,47].

Table 3. Optimum design results, of three-storey, two-bay steel frame

Three-story, two-bay frame		GAs (Kameshki and Saka, 2003 [26])				HS (Khalifa, 2011 [47])				ITHS (This study)			
Group	Member type	Rigid connection		Semi-rigid connection		Rigid connection		Semi-rigid connection		Rigid connection		Semi-rigid connection	
		Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
1	Column	W24x55	W24X55	W21x50	W18X36	W21X44	W21X48	W12X30	W18X40	W21X44	W21X44	W14X30	W14X30
2	Column	W21x44	W16X31	W18x35	W14X26	W14X30	W12X26	W12X26	W12X26	W14X30	W16X31	W12X26	W12X26
3	Column	W12x26	W12X40	W18x35	W8X18	W10X22	W10X22	W8X24	W8X21	W10X22	W10X22	W10X22	W10X22
4	Column	W30x108	W18X35	W27x84	W24X68	W14X38	W16X40	W14X48	W16X40	W14X38	W14X38	W16X45	W14X43
5	Column	W24x55	W18X35	W24x55	W24X68	W14X30	W12X30	W12X30	W12X30	W14X30	W12X30	W10X30	W12X30
6	Column	W18x35	W12X35	W18x46	W18X35	W10X22	W10X22	W12X30	W8X21	W10X22	W10X22	W8X24	W10X22
7	Beam	W14x26	W16X26	W18x35	W16X26	W16X26	W16X26	W16X26	W14X26	W16X26	W16X26	W16X26	W16X26
Total weight (lb)		8496	7404	9300	7092	6504	6528	6336	6300	6504	6528	6180	6132
Decrease weight (%)		27.26	17.18	33.54	13.54	4.98	6.06	2.46	2.67	4.98	6.06	0.00	0.00
Top story sway (inch)		0.48	0.64	0.39	0.61	0.78	0.63	1.13	0.93	0.78	0.82	1.14	1.18

Note: Allowable top story sway 1.44 inch

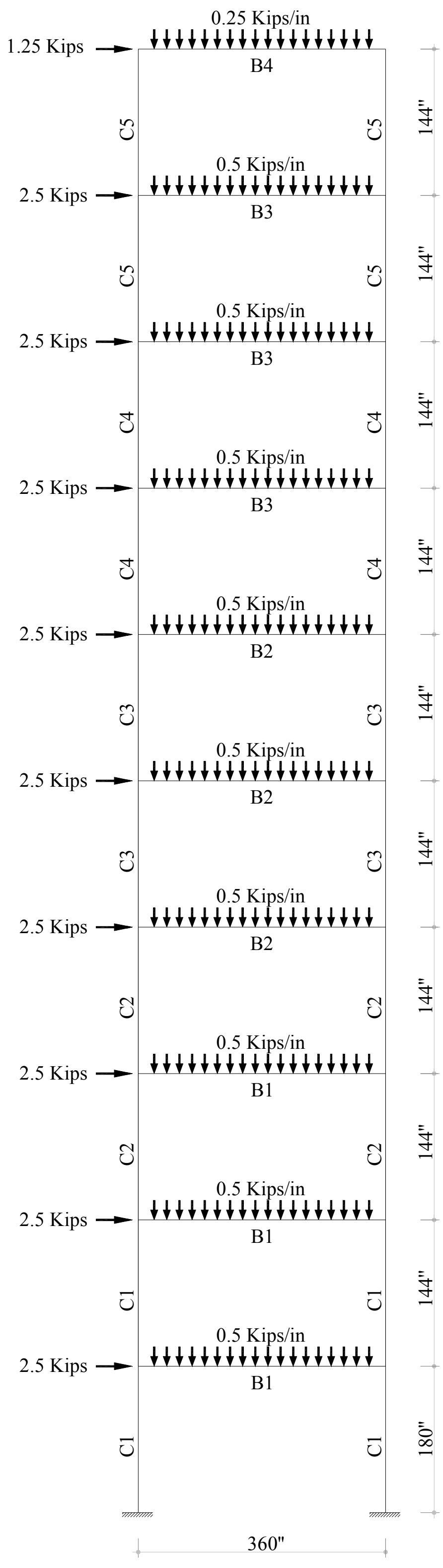

Fig. 5. Ten-storey, one-bay steel frame

The Modulus of Elasticity and Yield stress of the steel sections are 29,000 ksi and 36 ksi, respectively. The top storey and inter-storey sway (H/300) is limited to 4.92 inch, 0.48 inch, respectively. The allowable deflection for service imposed load (L/360) is considered 1.00 inch. The out-of-plane effective length factor for each column (Ky) is taken 1.0. The out of plane unbraced length (L/6) for beams is specified to be 60 inch. Bolt diameter and end plate thickness are taken to be 1.125 inch, 1.00 inch, respectively.

The following tuning parameters are applied in ITHS algorithm; the harmony memory size (HMS) and the harmony memory consideration rate (HMCR) are selected as 20 and 0.99 respectively. The minimum and maximum pitch adjustment rate PAR_{min} and PAR_{max} are taken as 0 and 1 respectively, the max improvisation (Max_{iter}) is 5000i^{th}. According to the HS algorithm not to be stuck in the local optimization, the selected parameters have been established by various trials, HMS = 20, HMCR = 0.90, PAR = 0.45, band width (bw) with a neighboring index of -2 or +2 [47].

The results of ten independent runs of the ITHS steel design optimization algorithm are presented in Table 4. It is observed that the linear analysis of semi-rigid connection frames less steel weight than those with rigid connections. The optimum weight converged at 3454th iterations after 67 minutes. And this means that the convergence was obtained using only 70% of the expected max improvisation (Max_{iter}), 5000.

In addition, the solution with non-linear analysis of semi-rigid connections showed 1.55%heavier frame weight than those with rigid connections due to the magnitude of loading and frame configuration. Over the above, Table 4 revealed that in all cases of the ITHS mean absolute percentage error (MAPE) of 0.81% - 2.02% was obtained, which reflected the accuracy of algorithm technique.

Fig. 6 shows a typical convergence history for an ITHS design of the ten-story, one-bay, steel frames with semi-rigid connections for the best solution. As shown in this figure, the optimization process decreased gradually to fine-tune. The continuous decrease in the values of pitch adjustments PAR and bandwidth (bw) prevent overshoot, oscillations and forcing the algorithm to focus more on intensification in the final iterations.

Table 4. Minimum steel frame weight of ten-storey, one-bay steel frame based on ITHS

Frame analysis no.	**Rigid connection**				**Semi-rigid connection**			
	Linear analysis		**Non-linear analysis plus P-Δ effect**		**Linear analysis**		**Non-linear analysis plus P-Δ effect**	
	Weight lb	**Iteration no.i^{th}**	**Weigh t lb**	**Iteration no.i^{th}**	**Weight lb**	**Iteration no.i^{th}**	**Weight lb**	**Iteration no.i^{th}**
1	48204	3369	47940	2493	48078	3454	48702*	2436
2	48324	2818	48036	2956	48138	3384	48702*	2565
3	48852	3212	48348	3333	48174	3278	48750	2736
4	49044	2976	48900	2877	48552	2822	48846	2934
5	49086*	3128	48996	2092	48576	3562	49038	3554
6	49086*	2813	49122	3418	48822	3521	49182	3657
7	49098	3042	49128	2390	48942	3219	49254	2676
8	49194	2636	49500	1767	49026	2835	49368	3473
9	49296	2699	49620	2160	49134	3118	49494	3325
10	49452	3203	49764	3352	49404	2664	49680	3266
Min weight (lb)	48204	-	47940	-	48078	-	48702	-
MAPE (%)	1.55	-	2.02	-	1.24	-	0.81	-
Time (min)	55		100		67		120	

*Note: 1- The * symbol have the same weights but different sections.*

To demonstrate the search behavior of the ITHS algorithm, Fig. 7 shows the variation in the size grouping of the Harmony memory (HM) matrix. Fig. 7 reveals that the harmony memory mean (HM^{mean}) smoothly decreases with iteration progress. The convergence curve showed that the difference between group A (intensification and diversification) and group B (diversification only) was high up to the iteration number 2000^{th}. This difference between group A and B diminished gradually beyond the iteration 2000^{th}, resulting in one value representing the harmony memory mean, group A and group B. This value was obtained at the iteration number 3454^{th} and kept unchanged until the 3636^{th} iteration. The addition iterations performed beyond the 3454^{th} iteration were carried out by the algorithm to ensure that no other minimums can be found.

The optimum steel sections designations obtained by the current Intelligent Tuned Harmony Search (ITHS) method – the GA results obtained by Kameshki and Saka (2003) and the HS results khalifa (2011) are given in Table 5. The optimum weight of frames with semi-rigid connections is generally less than that of frames with rigid connections. The optimum weight of semi rigid frames obtained using ITHS was 1.37% lower than those obtained by harmony search technique (HS). In addition, Table 5 revealed that in all cases ITHS yielded lighter frames between 0.83% - 1.53% compared with those obtained by HS [47].

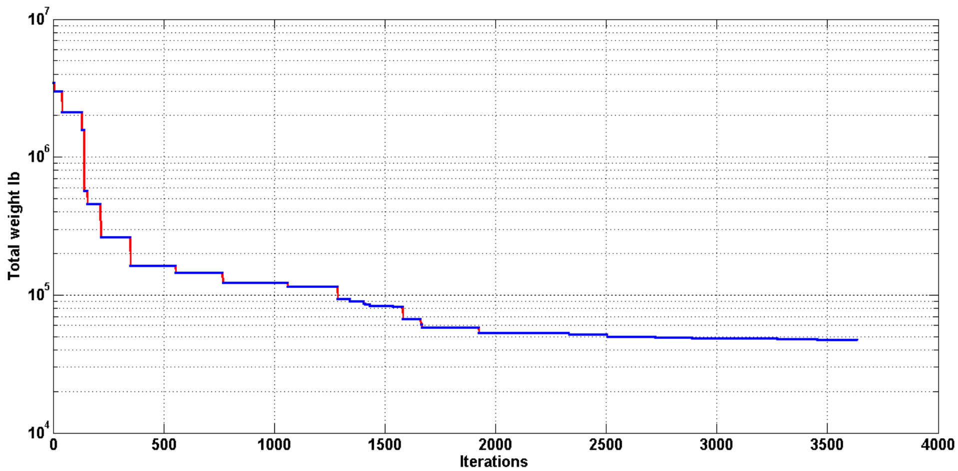

Fig. 6. Optimum design history for ten-storey, one-bay steel frame

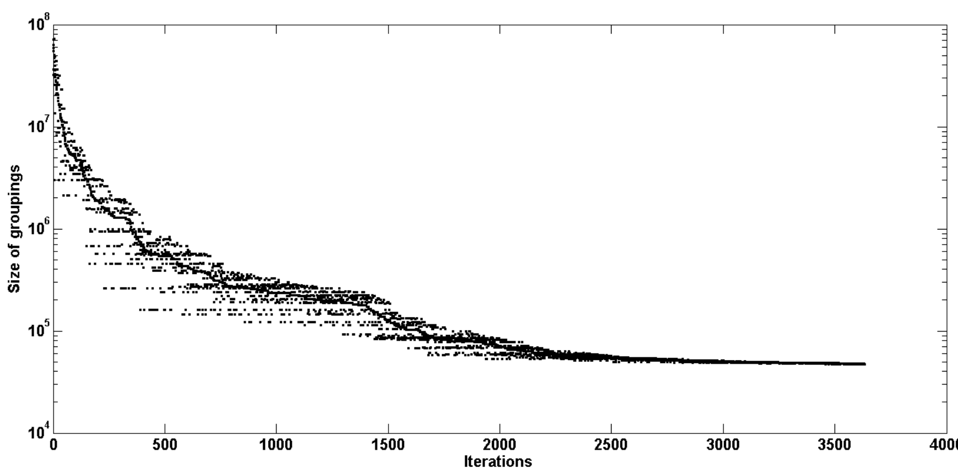

Fig. 7. Size of Grouping with iterations for ten-storey, one-bay steel frame

Table 5. Optimum design results, of ten-storey, one-bay steel frame

Ten story, one bay frame		GAs (Kameshki and Saka, 2003 [26])				HS (Khalifa, 2011 [47])				ITHS (This study)			
Group	Member type	Rigid connection		Semi-rigid connection		Rigid connection		Semi-rigid connection		Rigid connection		Semi-rigid connection	
		Linear	Non-linear	Linear	Non linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear	Linear	Non-linear
1	Column	W36x135	W36x182	W36x160	W36x182	W36X150	W36X150	W24X162	W33X152	W36X150	W36X150	W36X150	W36X150
2	Column	W33x141	W36x135	W36x135	W36x135	W30X132	W33X130	W24X131	W30X132	W33X130	W33X130	W30X124	W27X129
3	Column	W30x108	W30x108	W36x135	W33x118	W27X114	W33X118	W21X101	W30X108	W21X101	W30X108	W27X102	W27X102
4	Column	W27x102	W24x68	W33x118	W27x102	W24X84	W27X84	W14X82	W30X90	W18X86	W27X84	W27X84	W27X84
5	Column	W14x90	W21x111	W30x108	W14x99	W18X76	W24X68	W14X68	W27X84	W18X76	W24X68	W18X76	W24X84
6	Beam	W24x68	W24x68	W24x68	W33x118	W24X76	W24X76	W24X68	W24X68	W24X76	W24X76	W24X68	W24X68
7	Beam	W24x68	W24x68	W24x68	W24x76	W24X76	W24X76	W24X68	W24X68	W24X76	W24X76	W24X68	W24X68
8	Beam	W27x84	W24x68	W24x68	W21x93	W24X68	W24X68	W27X84	W24X76	W24X68	W24X68	W27X84	W24X84
9	Beam	W30x108	W21x44	W18x35	W18x50	W21X48	W21X44	W21X62	W18X65	W21X48	W21X44	W24X55	W21X55
Total weight (Ib)		51498	49764	51858	58950	48828	48420	48744	49110	48204	47940	48078	48702
Decrease weight (%)		6,64	2,13	7,29	17,38	1,53	-	1,3**7**	0,83	0,26	-	0.00	0.00
Top story sway (inch)		0.93	1.35	1.21	1.43	0.91	1.28	1.45	1.96	1.24	1.29	1.71	1.93

Note: Allowable top story sway 4.92 inch

When comparing the results of ITHS with the corresponding frames optimized using genetic algorithm (GA) technique, the ITHS indicated 7.29% lighter weights than those optimized using GAs. Furthermore, Table 5 revealed that in all cases ITHS yielded lighter frames between 2.13%-17.38% compared with those obtained by GAs [26].

The results also showed that the lateral displacement at the top storey was 1.71 inch in case of linear semi-rigid frame, which is higher than those obtained by HS and GAs, but within the allowable limit of AISC-LRFD (4.92 inch) [1]. This can be attributed to the fact that lighter sections will sway more than heavier members.

The obtained results of the ITHS optimization reflect the superiority of this algorithm in terms of accuracy, convergence speed, and robustness when compared with HS and GAs.

5. CONCLUSION

Optimum design of semi-rigid steel planar frame structures using an intelligent tuned harmony search (ITHS) algorithm has been achieved in this study. The following conclusions are drawn from the design examples when comparisons with harmony search (HS) and genetic algorithm (GA):

1. The designs with semi-rigid connection resulted in lighter frames than the ones with rigid connections. On the one hand, the total costs of the flexible connected frames are less than the rigidly connected frames. Moreover, it is observed that non-linear semi-rigid frames are lighter in some cases and heavier in others, compared to linear semi-rigid frames, depending on the magnitude of loading and frame configuration.
2. ITHS converges to optimum designs before the maximum number of frame analyses is executed in almost all designs 50% - 70% of the expected max improvisation. So the ITHS reflects the superiority in convergence speed than HS.
3. Mean absolute percentage error (MAPE) of 0.8% - 3% was obtained, which reflected the accuracy of ITHS algorithm technique.
4. ITHS reflect the effectiveness and robustness of the developed algorithm; it showed 0.8% - 6.06% lighter frame than that of HS and also 2.13% - 33.54% lighter frame than that of GAs.
5. The maximum sway obtained at the optimum design increases smoothly in case of semi-rigid frame in compression over that of the rigid frame. This can be attributed to the fact that lighter sections will sway more than the heavier members, but within the allowable limit by AISC-LRFD.
6. More economical optimum frames can be obtained by adjusting the stiffness of the connections.
7. This study is limited to design optimization of planar steel frame using AISC-LRFD code. Design optimization using three dimensional steel frames with other design codes is recommended for future studies.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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